Analysis of most important parts for silhouette-based gait recognition

Pratheepan Yogarajah, Joan V. Condell and Girijesh Prasad
Intelligent Systems Research Centre (ISRC), School of Computing and Intelligent Systems,
University of Ulster, United Kingdom.

***Abstract*—Many silhouettes based features are proposed for gait recognition. But these methods suffer with covariate factors such as clothing and carrying objects. These covariate factors mostly attached with silhouettes and make gait recognition much difficult. Therefore we proposed a new silhouette based feature to analyse the influence of body parts and increase the recognition rate for individual identification.**

I. Introduction

Gait recognition methods can be mainly classified into two categories: model-based and appearance-based. The computational cost of model-based methods is relatively high compared to appearance-based methods [1]. In the literature, cost effective appearance-based features are considered in gait recognition.

In appearance-based methods, the Gait Energy Image (GEI) [2] has been proven to be the most effective. While GEI can attain good performance under normal gait sequences, it is sensitive to covariate factors, such as clothing and carrying of objects. It does not work well when clothing and carrying objects cause much individual variations. Therefore different gait feature representations have been proposed in the literature, Enhanced GEI (EGEI)[3], Active Energy Image (AEI)[4], Gait Entropy Image (GEnI)[5], M_G[6], to overcome the affect of different clothing and carrying object covariate factors, see Figure 1. Even though their average recognition rates are not that promising (i.e. less than 75%). This indicates that covariate factors are still attached with those gait features.

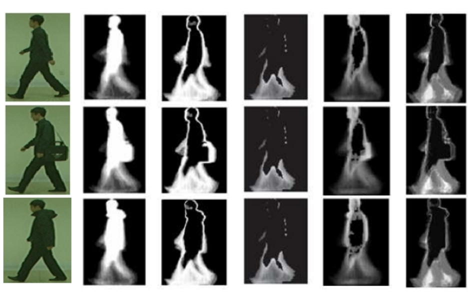

Fig. 1. shows different gait features for a particular individual from CASIA gait dataset. Columns from left to right represent original image, GEI, GEnI, M_G, EGEI and AEI respectively. Rows from top to bottom represent normal, carrying bag and wearing coat conditions walking.

It can be seen from Figure 1 that covariate factors are also considered as part of body. Li et.al. [8] analysed the removal of different body parts of GEI for gait recognition. They obtained the information of the gait from the motions of the different parts of the silhouette. The human silhouette is segmented into seven components, namely head, arm, trunk, thigh, front-leg, back-leg, and feet, see Figure 2. In their experiment, they showed that removal of certain body decrease the recognition rate, e.g. head and also removal of some parts increased the recognition rate, e.g. thigh. A predefined template is used to remove the body parts from GEI. Instead, we propose a new silhouette based gait feature using Poisson Random Walk (PRW) to remove certain body parts on binary image and analyse the recognition rate. Our proposed method is given in Section II. In Section III, recognition algorithm and the experimental results are presented. Finally Section IV gives the conclusion to the work.

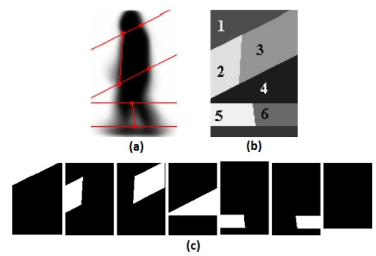

Fig. 2. Body parts and correspondent templates [8]

II. Our Method

Recently, Poisson Random Walk (PRW) [9] approached is proposed with a useful application: separate the parts of binary silhouettes. Consider a shape as a given silhouette S in a grid plane (a binary image) and ∂S a simple closed curve as its boundary. The PRW approach assigns a value to every pixel of the silhouette [9]. At pixel p we can move to one of its immediate four neighbors (at each step). Let $U(x, y)$ be defined as the expected number of steps taken for a random walk started at point (x, y) to hit the boundary. Therefore we can write:

$$U(x,y) = \frac{1}{4}(U(x+1,y) + U(x-1,y) + U(x,y+1) + U(x,y-1)) + 1 \quad (1)$$

This is the discrete form of the following Poisson equation with Drichlet boundary condition on ∂S. $U(x, y)$ can be computed recursively as follows: At the boundary of S, i.e., $(x, y) \in \partial S$, $U(x, y) = 0$. At every point (x, y) inside S,

$U(x,y)$ is equal to the average value of its immediate four neighbours plus a constant (representing the amount of time required to get to an immediate neighbour).

As mentioned in [9], we can use Poisson equation to extract variety of useful properties of a binary silhouette. Some of these properties are extracted from U and its gradient. We define the function Φ as, $\Phi(x,y) = U(x,y) + \parallel \nabla U(x,y) \parallel^2$. Therefore, Φ has a distinctive characteristic to separate different parts of a shape based on their thickness. However, to get the better separation for thresholding, it is desirable to separate the intensity values for the different parts better. Therefore the natural logarithm is taken, $\Psi = log(\Phi)$. Then Ψ is scaled to make its values ranges from 0 to 255. Figure 3 (a), (b) and (c) show U, Φ and Ψ respectively.

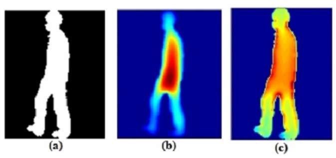

Fig. 3. (a) represents binary silhouette. (b) represents U of (a). (c) represents computed Ψ.

Pixel coordinate positions corresponding to pixel values greater than θ are selected from Ψ. Then the selected pixels coordinate positions which correspond to the pixel values of Figure 3(a) are changed to 0 and the PRW silhouette (PRW$_{sil}$) is generated, see Figure 4.

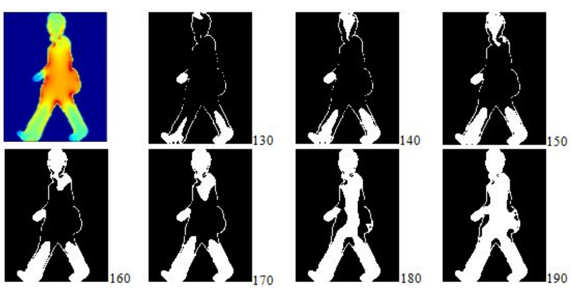

Fig. 4. top left represents Ψ and rest represent PRW$_{sil}$ for different θ values.

Then a sequence of PRW$_{sil}$ for a gait period is considered to calculate the final P$_{RW}$GEI feature. P$_{RW}$GEI is calculated as, $P_{RW}GEI(x,y) = \sum_{n=1}^{N} PRW_{sil}^{n}(x,y)$, where PRW_{sil}^{n} is a PRW_{sil} of the n^{th} frame of N number of frames in a particular gait period. Figure 5 shows P$_{RW}$ GEI features of sample of three individuals from CASIA-B database.

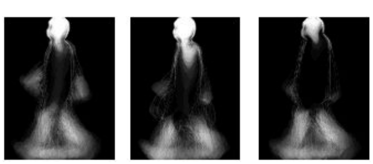

Fig. 5. shows PRW-GEI obtained with $\theta = 160$ for three individuals.

III. Recognition and Results

(PCA + LDA) [5] is applied on the calculated P$_{RW}$GEI, which aims to find a subspace where data from different classes are best separated in a least square sense. The 1-NN is applied as classifier for gait recognition. We used the CASIA-B dataset (124 subjects with normal, clothing and carrying conditions) to evaluate the proposed algorithm. We used the same experimental setup as proposed in [5], [4] and [6].

TABLE I
Performance on CASIA-B (covariate) dataset

$\theta =$	130	140	150	160	170	180
CasiaSetA2	98.0%	98.0%	98.0%	98.4%	98.3%	98.7%
CasiaSetB	86.3%	86.3%	90.0%	93.1%	92.3%	88.9%
CasiaSetC	42.3%	39.1%	37.9%	44.4%	44.0%	44.3%
Average	75.6%	74.4%	75.3%	78.6%	78.2%	77.3%

It can be seen from Table I that when θ increase from 130 to 180, there is not much changes in normal gait recognition (i.e. CasiaSetA2). Gait recognition for carrying object (i.e. CasiaSetB) steadily increases until 160 then decreases. On the other hand, gait recognition for clothing (i.e. CasiaSetC) is almost same for θ for 160 to 180.

IV. Conclusion

In this paper, a novel P$_{RW}$GEI appearance based gait feature representation has been proposed for gait recognition. Experimental results showed that the performance of the proposed algorithm is promising. The proposed method provides recognition rate greater than 78% for θ values 160 and 170. This is a better recognition rate than [5], [4] and [6]. However, we have only tested our algorithm with CASIA-B dataset. Therefore as a future direction, we would like to test out method with other dataset, such as USF database and SOTON database. In addition, further research can be done to find a robust analytical solution to identify the optimal value for θ.

References

[1] L. Wang., T. N. Tan., W. M. Hu and H. Z. Ning. Automatic Gait Recognition Based on Statistical Shape Analysis, *IEEE Trans. on Image Processing*, Vol. 12(9), pp. 1120–1131, 2003.

[2] J. Han and B. Bhanu. Individual recognition using gait energy image. *Trans. on PAMI*, 28(2):316–322, 2006.

[3] X. Yang, Y. Zhou, T. Zhang, G. Shu and J. Yang, (2008) Gait recognition based on dynamic region analysis, *Signal Processing*, 88, pp. 2350-2356.

[4] E. Zhang, Y. Zhao and W. Xiong. (2010) Active energy image plus 2DLPP for gait recognition, *Signal Processing*, 90 (7) , pp. 2295-2302.

[5] Bashir, K., Xiang, T., Gong, S. (2009) Gait recognition using gait entropy image. *3rd International Conference on Crime Detection and Prevention (ICDP)*, pp. 1–6.

[6] Khalid Bashir, Tao Xiang, Shaogang Gong. (2010) Gait recognition without subject cooperation. *PR Letters*, 31(13): 2052–2060.

[7] M. Altab Hossain, Y. Makihara, J. Wang, and Y. Yagi. Clothing-invariant gait identification using part-based clothing categorization and adaptive weight control. *Pattern Recognition*, 43:2281–2291, 2010.

[8] X. Li, S. J. Maybank, S. Yan, D. Tao and D. Xu. Gait Components and Their Application to Gender Recognition, *IEEE Transactions On Systems, Man, And Cybernetics Part C: Applications And Reviews*, Vol. 38, No. 2, pp. 145–155, 2008.

[9] L. Gorelick and M. Galun and E. Sharon and R. Basri and A. Brandt, Shape Representation And Classification Using The Poisson Equation, *IEEE Transactions On PAMI*, Vol. 28, No. 12, 2006.